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Remote sensing and automated monitoring systems (AMS) for Insect pest detection and surveillance (IDPS)

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Abstract

Insect pests represent a major challenge to agricultural productivity, necessitating efficient monitoring and control methods. Recent progress in remote sensing and automated surveillance technologies has opened new possibilities for early detection and ongoing observation of pest activity in farming environments. This paper reviews the latest developments in these areas, focusing on satellite imaging, unmanned aerial vehicles (UAVs), wireless sensor networks, and machine learning techniques used for identifying insect pests. The benefits, constraints, and practical uses of these tools in precision agriculture and integrated pest management are examined. Real-world examples demonstrate successful applications of such systems in monitoring key insect pests. Additionally, the paper identifies key challenges and future research needs in creating monitoring solutions that are affordable, scalable, and dependable. Combining remote sensing and automated monitoring with decision support systems and targeted pest control strategies offers strong potential to enhance crop protection and support sustainable food production amid growing pest threats.

Keywords: Remote sensing, automated monitoring, insect pests, precision agriculture, integrated pest management

Introduction

Insect pests pose a serious challenge to agriculture, leading to substantial reductions in crop yields and significant economic losses globally. Annual crop losses attributed to these pests are estimated at 20-30% (Oerke, 2006) ^[29]. To reduce damage and support food security, it is essential to monitor and manage pest populations effectively. Conventional approaches, such as field inspections and the use of sticky traps, tend to be labor-heavy, slow, and often unable to deliver prompt or precise data on pest activity (Pimentel, 2009) ^[30]. Additionally, their limited spatial reach and detail make large-scale pest detection and tracking difficult. Recent progress in remote sensing and automated monitoring has created new opportunities for early pest detection in farming systems. Technologies like satellite imaging, drones, and hyperspectral sensors allow for non-intrusive, wide-area assessment of both crop conditions and pest outbreaks (Zhang *et al.*, 2019) ^[28]. Meanwhile, automated tools such as wireless sensor networks, sound-based detection systems, and computer vision enable real-time, continuous observation of pest numbers and behaviors (Jiang *et al.*, 2018) ^[31]. The combination of remote sensing, automated monitoring systems, and precision agriculture technologies along with decision support tools holds significant promise for transforming pest management approaches. Precision agriculture relies on advanced tools such as global positioning systems (GPS), geographic information systems (GIS), and variable rate application (VRA) to enhance crop productivity and improve resource efficiency (Gebbers & Adamchuk, 2010) ^[32]. When data from remote sensing and automated monitoring with these technologies, farmers can implement more precise pest control measures, minimising dependence on broad-spectrum pesticides and supporting more sustainable practices. This paper offers a detailed review of current remote sensing and automated monitoring methods used for detecting and tracking insect pests. It examines the underlying principles, real-world applications, benefits, and constraints of these technologies. Examples of successful deployments in managing key insect pests are included to illustrate practical outcomes. The discussion also covers how these monitoring systems can be effectively combined with precision

agriculture and decision-making tools. Lastly, the paper identifies existing challenges and suggests future research priorities for creating monitoring solutions that are affordable, scalable, and dependable.

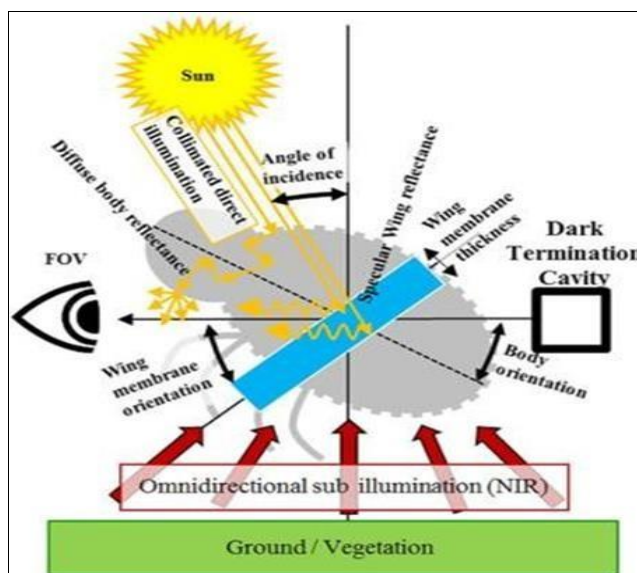


Fig 1: Insect scattering

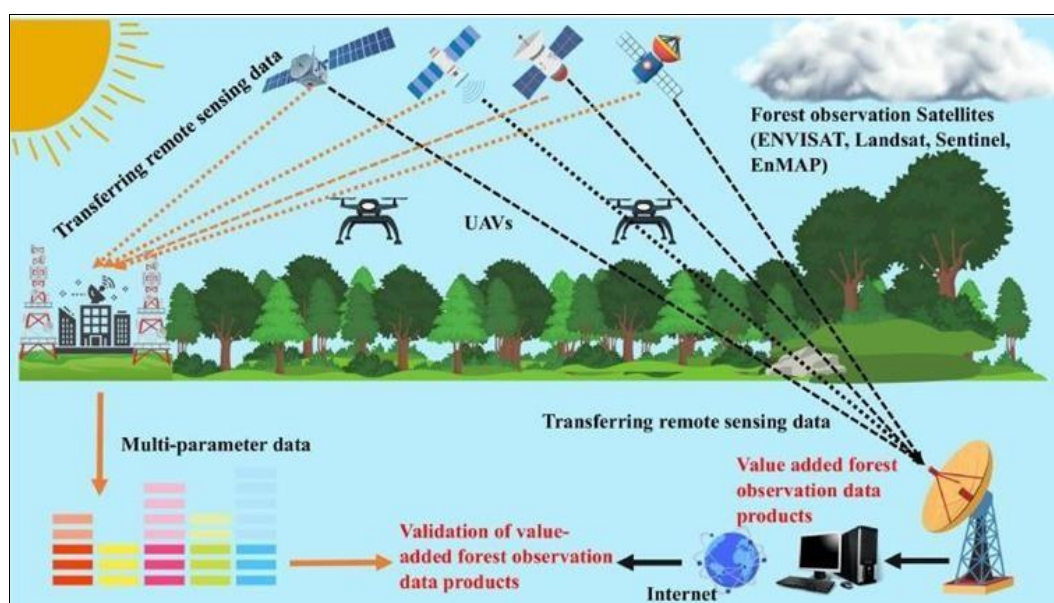


Fig 2: Use of Satellites for Forest observation

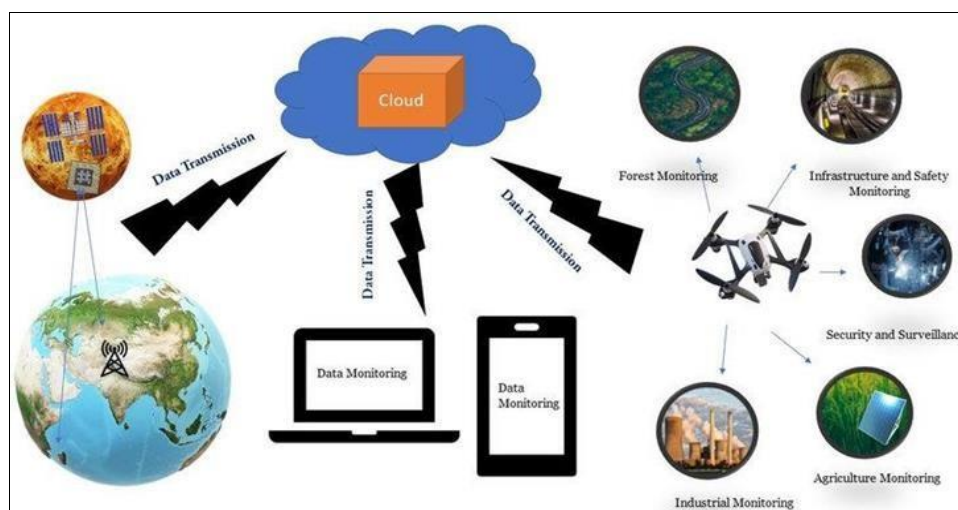


Fig 3: Integration of remote sensing and automated monitoring systems

2. Remote sensing techniques for insect pest detection

Remote sensing has become an effective approach for tracking crop conditions and identifying insect pest outbreaks across different spatial and temporal scales. It relies on collecting and interpreting data from sensors carried by satellites, aircraft, or unmanned aerial vehicles (UAVs). The combination of spectral, spatial, and temporal detail in these data enables the recognition of minor changes in plant health and helps pinpoint areas affected by pests (Zhang *et al.*, 2019). This section outlines the underlying principles, practical uses, benefits, and constraints of using satellite imagery, UAVs, and hyperspectral imaging in detecting insect pests. Satellite imagery is commonly used to monitor crop conditions and identify insect pest outbreaks across broad regional or global areas. Sensors like Landsat, MODIS, and Sentinel capture multispectral data with differing spatial and temporal resolutions (Zhang *et al.*, 2019). Their spectral bands, especially in the visible and near-infrared ranges, respond to variations in plant health and support the calculation of vegetation indices such as NDVI and EVI (Huang *et al.*, 2018). These tools are useful for pest detection because crops affected by insects often display unique spectral patterns compared to healthy ones. For example, wheat fields infested with aphids tend to show reduced NDVI values due to lower chlorophyll levels and diminished leaf area (Mulla *et al.*, 2017). Likewise, infestations of red palm weevil (*Rhynchophorus ferrugineus*) in date palms have been identified through satellite observations of altered spectral reflectance in affected trees (Javeedalee *et al.*, 2019). A key strength of satellite monitoring is its capacity to cover extensive regions and deliver repeated observations, enabling tracking of pest spread and pinpointing areas needing intervention. However, limitations exist spatial resolution may

be too coarse to detect minor infestations or individual pests, and factors like cloud cover, atmospheric interference, and canopy structure can affect detection accuracy (Zhang *et al.*, 2019). Despite these challenges, several studies highlight successful applications. Mulla *et al.* (2017) used Landsat data to identify Russian wheat aphid (*Diuraphis noxia*) outbreaks in U.S. wheat fields, noting significantly lower NDVI in infested areas, suggesting promise for early detection. Similarly, (Javeedalee *et al.*, 2019) applied SPOT-6 imagery to detect red palm weevil in UAE date palm plantations, creating a spectral index using red and near-infrared bands that effectively distinguished healthy from infected trees ^[28].

2.1 Satellite Imagery

Satellite imagery is commonly employed to assess crop conditions and identify insect pest outbreaks across broad regional or global areas. Sensors like those on Landsat, MODIS, and Sentinel satellites capture multispectral data with differing spatial and temporal resolutions (Zhang *et al.*, 2019). These sensors detect light in the visible and near-infrared ranges, which are particularly responsive to variations in plant health. This information supports the calculation of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), both widely used indicators of vegetation status (Huang *et al.*, 2018). Detecting insect pests via satellite relies on the fact that affected crops often display unique spectral patterns compared to healthy ones. For example, wheat fields infested with aphids tend to show reduced NDVI values due to diminished chlorophyll levels and leaf coverage (Mulla *et al.*, 2017) ^[28, 33, 34, 39].



Fig 4: Remote sensing techniques for insect pest detection

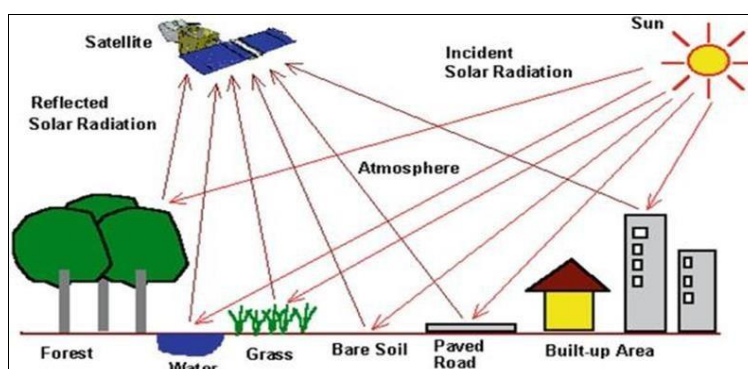


Fig 5: Satellite imagery for monitoring crop health

Likewise, infestations of red palm weevil (*Rhynchophorus ferrugineus*) in date palms have been identified by analyzing shifts in the spectral reflectance of infected trees (Javeedalee *et al.*, 2019). A key strength of satellite-based monitoring is its capacity to survey vast areas repeatedly over time, enabling tracking of pest spread and pinpointing high-risk zones for focused intervention. However, limitations exist such as insufficient resolution for spotting small or isolated infestations and factors like cloud cover, atmospheric interference, and canopy complexity can affect detection accuracy (Zhang *et al.*, 2019).

Numerous studies highlight successful applications of this technology. (Mulla *et al.* 2017) utilized Landsat data to monitor Russian wheat aphid (*Diuraphis noxia*) outbreaks in U.S. wheat fields, observing notably lower NDVI readings in affected areas, suggesting promise for early detection. In another example, (Javeedalee *et al.* 2019) applied SPOT-6 imagery to identify red palm weevil damage in date palm groves in the United Arab Emirates. They created a spectral index using red and near-infrared bands that effectively distinguished between healthy and infested trees [28, 33, 34].

2.2 Unmanned Aerial Vehicles (UAVs)

Unmanned aerial vehicles (UAVs), commonly referred to as drones, have become increasingly valuable for monitoring insect pests in agriculture with high resolution and adaptability. These systems can carry a range of sensors such as RGB, multispectral, and thermal cameras to collect detailed images of crop canopies and individual plants (Maes & Steppe, 2019). The low-altitude flights and fine spatial resolution (down to the centimeter scale) of UAV imagery make it possible to spot early signs of pest activity and even identify specific insect species. UAVs used in pest monitoring generally fall into two categories: fixed-wing and rotary-wing models. Fixed-wing drones offer longer flight durations and are better suited for covering large agricultural areas efficiently. In contrast, rotary-wing drones like quadcopters and hexacopters provide superior maneuverability

and the ability to hover, allowing for close-up observations of particular plants or localized infestations (Maes & Steppe, 2019).

The choice of sensor depends on the pest and crop being monitored. RGB cameras are widely used to visually assess damage and identify pest life stages, such as eggs, larvae, or adults. Multispectral sensors capture data across several wavelengths, enabling the calculation of vegetation indices that reveal changes in plant health caused by pests. Thermal sensors detect temperature differences in crops, which can signal stress or disease resulting from pest attacks (Maes & Steppe, 2019). Processing UAV data typically involves image pre-processing (e.g., orthorectification, mosaicking, radiometric calibration) to ensure consistency (Zhang *et al.*, 2019), followed by feature extraction methods like texture analysis, edge detection, or objectbased image analysis (OBIA) to locate affected areas. Machine learning techniques such as support vector machines (SVM), random forests (RF), and convolutional neural networks (CNN) are then applied to classify and map infestations based on these features (Ghosh *et al.*, 2021). Several real-world applications highlight the effectiveness of UAVs in pest monitoring. (Hoffmann *et al.* 2021), for instance, employed RGB imagery from drones to detect European corn borer (*Ostrinia nubilalis*) infestations in maize, using a CNN model to distinguish between healthy and damaged plants with high accuracy. Similarly, Kalischuk *et al.* (2022) utilized multispectral drone data to track wheat stem sawfly (*Cephus cinctus*) infestations in wheat fields, showing that indices like Normalized Difference Red Edge (NDRE) could effectively differentiate infested from healthy plants. Key benefits of UAV-based pest monitoring include fine image detail, operational flexibility, and rapid coverage of extensive areas, supporting timely and precise pest management. However, challenges remain, including operational expenses, regulatory constraints, and the complexity of processing large volumes of image data (Maes & Steppe, 2019) [28, 35, 36].

Table 1: Satellite Sensors for Insect Pest Detection

Sensor	Spatial Resolution	Temporal Resolution	Spectral Bands	Application Examples
Landsat	30 m	16 days	11	Aphid detection in wheat, Red palm weevil detection in date palm
Modis	250 m - 1 km	Daily	36	Locust outbreak monitoring, Armyworm detection in maize
Sentinel	10 m - 60 m	5 days	13	Bark beetle detection in forests, Whitefly monitoring in cotton

Table 2: Sensors used in UAVs for insect pest detection

Sensor	Spectral Bands	Spatial Resolution	Application Examples
RGB Camera	3 (Red, Green, Blue)	Centimeter-level	Visual inspection of pest damage, Identification of pest stages
Multispectral Camera	4-10	Centimeter-level	Vegetation index calculation, Plant health monitoring
Thermal Camera	1 (Infrared)	Centimeter-level	Detection of pest-induced stress, Disease monitoring

Table 3: Comparison of hyperspectral and multispectral imaging for insect pest detection

Imaging Technique	Number of Bands	Spectral Resolution	Advantages	Limitations
Hyperspectral Imaging	Hundreds	Narrow (2-10 nm)	Detailed spectral information, High discrimination power	High data dimensionality, Complex processing, High cost
Multispectral Imaging	4-10	Wide (20-100 nm)	Simpler data processing, Lower cost	Limited spectral information, Lower discrimination power

2.3 Hyperspectral and Multispectral Imaging

Hyperspectral and multispectral imaging have demonstrated significant promise in identifying insect pest infestations by analyzing the unique spectral signatures of affected plants. Hyperspectral imaging collects data across hundreds of narrow, contiguous wavelength bands, offering detailed spectral profiles of plant conditions. In contrast, multispectral imaging uses a

smaller number of bands usually between four and ten carefully chosen to enhance the ability to distinguish specific features (Zhang *et al.*, 2019). These imaging methods work on the principle that plants under pest stress display measurable changes in their spectral reflectance compared to healthy ones. Such differences arise from alterations in leaf pigments, water content, and internal cell structure caused by feeding or infection

(Huang *et al.*, 2018). For example, wheat leaves damaged by aphids show reduced reflectance in the near-infrared range and increased reflectance in the visible spectrum relative to uninfested leaves (Yuan *et al.*, 2014). These imaging techniques are applied using ground-based sensors, drones, or satellites to capture high-resolution spectral data from crop canopies. The collected data is then analyzed using tools like vegetation

indices, spectral angle mapping, and machine learning models to detect and map areas affected by pests (Zhang *et al.*, 2019). A key challenge lies in identifying the most effective spectral bands or indices that respond specifically to certain pests or diseases, which requires in-depth knowledge of both pest biology and host plant characteristics. Additionally, the large volume of data generated by hyperspectral systems [28, 38, 39]



Fig 6: Unmanned aerial vehicles for pest monitoring

creates difficulties in storage, processing, and interpretation (Huang *et al.*, 2018). Recent research highlights successful applications across different crops. Yuan *et al.* (2014) employed hyperspectral imaging to assess aphid levels in wheat, pinpointing sensitive spectral indicators and building a predictive model for estimating pest density. Likewise, Ishimwe *et al.* (2014) used multispectral data to identify tomato leafminer (*Tuta absoluta*) infestations, showing that the ratio of near-infrared to red reflectance effectively separated healthy from infected leaves. Despite these advances, widespread adoption remains limited due to the expense and technical demands of current imaging systems. Future efforts should prioritize developing more affordable, accessible sensors that integrate smoothly into routine pest monitoring. Combining spectral data with complementary information such as weather patterns and crop development models could also enhance understanding of

pest behavior and improve forecasting accuracy (Zhang *et al.*, 2019) [28, 38, 39].

3. Automated monitoring systems for insect pest surveillance

Automated monitoring systems have become a valuable solution for continuously tracking insect pest populations in agriculture, offering real-time surveillance capabilities. These systems rely on a range of technologies including wireless sensor networks, acoustic sensors, and computer vision to gather data on pest behavior, activity levels, and surrounding environmental factors. By applying sophisticated algorithms to this data, it becomes possible to generate practical insights that support more informed pest management strategies. This section explores the underlying principles, practical uses, benefits, and constraints associated with these three key technologies in the context of monitoring agricultural pests.

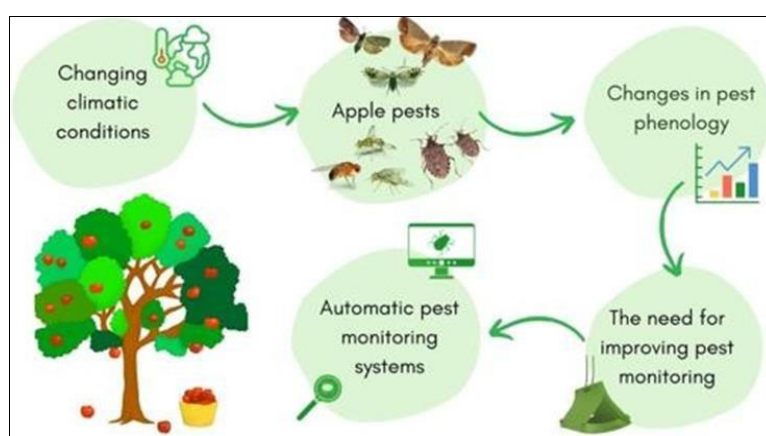


Fig 7: Automated monitoring systems for insect pest surveillance

3.1 Wireless Sensor Networks

Wireless sensor networks (WSNs) are made up of numerous small, affordable, and energy-efficient sensor nodes spread across agricultural fields to monitor environmental conditions and signs of pest activity (Jiang *et al.*, 2018). These nodes contain sensors that measure factors like temperature, humidity, light, and CO₂ levels conditions that can influence pest development. The nodes

exchange data wirelessly using protocols such as ZigBee or LoRa, linking together and connecting to a base station through a multi-hop communication structure (Chisimba *et al.*, 2022). A typical WSN setup for pest monitoring includes three core components: sensor nodes, gateway nodes, and a central server. Sensor nodes gather data and perform basic processing locally, while gateway nodes relay information between the sensors and

the central server. The central server receives this data, conducts in-depth analysis, and generates visual outputs for interpretation (Jiang *et al.*, 2018). Sensors used in these networks fall into two general types: direct and indirect. Direct sensors, including camera traps and acoustic detectors, capture evidence of pests directly such as images or sounds. Indirect sensors track environmental variables like temperature, humidity, and light, which can indicate favorable conditions for pest growth and movement (Shah *et al.*, 2022). Efficient data transmission and power use are essential in WSNs due to the limited battery life and computing capacity of sensor nodes. To extend network operation and maintain reliable communication, techniques like duty cycling and data aggregation are commonly applied (Jiang *et al.*, 2018). Duty cycling conserves energy by switching nodes between active and low-power sleep states, while data aggregation minimizes transmitted data volume by summarizing or compressing readings before sending (Chisimba *et al.*, 2022). Real-world applications have shown the effectiveness of WSNs in monitoring insect pests across various crops. For instance, (Jiang *et al.* 2018) implemented a system to track the rice brown planthopper (*Nilaparvata lugens*) using sensors for temperature, humidity, light, and imaging. Data were sent to a cloud platform for processing, allowing real-time tracking of pest populations and early detection of outbreaks. In another example, (Shah *et al.* 2022) deployed a WSN with acoustic sensors in date palm groves to detect sounds from red palm weevils (*Rhynchophorus ferrugineus*) during feeding and mating, helping estimate infestation levels and guide precise interventions. Key benefits of WSNs in pest monitoring include continuous, real-time data collection, adaptability to different field sizes and layouts, and compatibility with other precision farming tools like variable-rate application systems (Jiang *et al.*, 2018). Nonetheless, challenges remain, such as exposure to tough field conditions, the need for frequent battery changes, and risks of sensor malfunctions or communication breakdowns (Chisimba *et al.*, 2022) [2, 16, 31].

3.2 Acoustic Detection Systems

Acoustic detection systems have become a promising method for monitoring insect pests by capturing and analyzing their species-specific sounds and vibrations. Numerous insect species generate unique acoustic signals during activities such as feeding, mating, or communication, which can be recorded using microphones or piezoelectric sensors (Mankin *et al.*, 2011). These systems work by collecting sound data, then applying signal processing and pattern recognition techniques to identify pest species and assess their population levels (Koubaa *et al.*, 2021). This technology has been successfully applied in various agricultural settings, including grain storage units, orchards, and vineyards. For instance, pests like the rice weevil (*Sitophilus oryzae*) and the red flour beetle (*Tribolium castaneum*) have been detected in stored grain by recording the sounds they produce while feeding and moving (Mankin *et al.*, 2011). In citrus orchards, acoustic sensors have also proven effective in identifying the Asian citrus psyllid (*Diaphorina citri*), a key carrier of citrus greening disease (Mankin *et al.*, 2019) [10, 11]. A crucial aspect of these systems is the development of sound recognition algorithms. These tools analyze key features of the recorded signals such as timing and frequency patterns to classify them according to pest type or behavior (Koubaa *et al.*, 2021). Machine learning methods, including support vector machines (SVM), hidden Markov models (HMM), and deep neural networks, have shown strong performance in accurately identifying insect sounds (Potamitis *et al.*, 2022). A major

benefit of acoustic monitoring is its non-intrusive nature, enabling real-time tracking without visual checks or direct contact. It supports early pest detection, population estimation, and assessment of pest control efforts (Mankin *et al.*, 2019). Nevertheless, challenges remain, including interference from background noise, sounds from non-target insects, and natural variations in how insects produce sound (Koubaa *et al.*, 2021) [7, 11, 13].

3.3 Computer Vision and Machine Learning Techniques

Computer vision and machine learning techniques have gained significant attention for automated insect pest monitoring in recent years. These techniques involve the acquisition of digital images or videos of insect pests using cameras or smartphones, followed by image processing and analysis using advanced algorithms (Biswas *et al.*, 2022). The principles of computer vision for pest detection rely on the extraction of visual features, such as color, shape, texture, and motion, from the images or videos, which are then used to identify and classify the insect pests (Kour *et al.*, 2022). Image processing algorithms for pest detection typically involve a series of steps, including image pre-processing, segmentation, feature extraction, and classification. Image pre-processing techniques, such as noise reduction, contrast enhancement, and color space transformation, are applied to improve the quality and consistency of the images (Biswas *et al.*, 2022). Image segmentation algorithms, such as [1, 8]

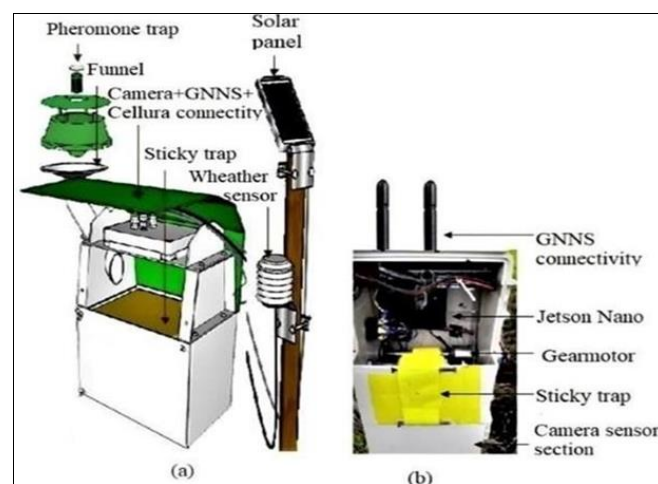


Fig 8: Remote monitoring devices

thresholding, edge detection, and region growing, are used to separate the regions of interest (i.e., insect pests) from the background (Kour *et al.*, 2022). Feature extraction techniques, such as scale-invariant feature transform (SIFT), histogram of oriented gradients (HOG), and local binary patterns (LBP), are employed to extract distinctive features from the segmented regions (Biswas *et al.*, 2022). Machine learning algorithms, such as support vector machines (SVM), random forests (RF), and convolutional neural networks (CNN), are widely used for automated insect pest classification based on the extracted features. These algorithms learn from labeled training data and build models that can classify new images or videos into different pest species or damage levels (Kour *et al.*, 2022). Deep learning architectures, particularly CNNs, have shown remarkable performance in insect pest classification tasks due to their ability to automatically learn hierarchical features from large datasets (Nath *et al.*, 2021). Several case studies have demonstrated the successful application of computer vision and

machine learning techniques for insect pest monitoring in various crop systems. For instance, (Nath *et al.* 2021) developed a CNN-based system for the detection and classification of the rice brown planthopper (*Nilaparvata lugens*) in rice fields. The system achieved an accuracy of 98.7% in classifying the planthopper from field- captured images, outperforming traditional machine learning algorithms such as SVM and RF. Similarly, (Kour *et al.* 2022) used a combination of image processing and machine learning techniques to detect and classify the damage caused by the tomato leafminer (*Tuta absoluta*) in tomato plants. The system achieved an accuracy of

96.3% in classifying the damage levels based on the extracted color and texture features. The main advantages of computer vision and machine learning techniques for insect pest monitoring include their high accuracy, automation potential, and scalability. These techniques can process large volumes of image data and provide real-time information on pest infestations, enabling timely and targeted control measures (Biswas *et al.*, 2022). However, the performance of these techniques depends on the quality and diversity of the training data, the selection of appropriate features and algorithms, and the computational resources available (Kour *et al.*, 2022) ^[1, 8, 12].

Table 4: Sensors used in wireless sensor networks for insect pest monitoring

Sensor Type	Parameters Measured	Application Examples
Temperature Sensor	Air and soil temperature	Monitoring of pest development rates, Prediction of pest outbreaks
Humidity Sensor	Relative humidity	Monitoring of pest habitat suitability, Prediction of fungal disease outbreaks
Light Sensor	Light intensity, Photoperiod	Detection of pest activity patterns, Monitoring of crop growth stages
CO ₂ Sensor	CO ₂ concentration	Monitoring of plant stress, Detection of pest respiration
Camera Trap	Insect images, Videos	Identification of pest species, Monitoring of pest activity and behavior
Acoustic Sensor	Insect sounds, Vibrations	Detection of pest feeding and mating activities, Estimation of pest population density

Table 5: Machine learning algorithms for automated insect pest classification

Algorithm	Principle	Advantages	Limitations
Support Vector Machines (SVM)	Finds optimal hyperplane to separate classes	Works well with small datasets, Handles high-dimensional data	Sensitive to noisy data, Difficult to interpret
Random Forests (RF)	Ensemble of decision trees, Majority voting	Handles large datasets, Robust to overfitting	Computationally expensive, Prone to bias
Convolutional Neural Networks (CNN)	Learns hierarchical features from images	High accuracy, Automatic feature extraction	Requires large labeled datasets, Computationally intensive

Table 6: Advantages and limitations of remote sensing and automated monitoring systems for insect pest management

Advantages	Limitations
Early detection of pest infestations	High initial costs and technical expertise required
High spatial and temporal resolution	Dependence on weather conditions and data quality
Non-destructive and non-invasive monitoring	Limited ability to detect low-density pest populations
Scalability and flexibility in deployment	Potential for false positives and false negatives
Integration with precision pest control strategies	Data management and interpretation challenges
Economic and environmental benefits	User acceptance and adoption barriers

4. Integration of remote sensing and automated monitoring systems: Combining remote sensing with automated monitoring systems enables a detailed, multi-level approach to detecting and tracking insect pests. Integrating data from satellites, unmanned aerial vehicles (UAVs), wireless sensor networks, and computer vision allows for a more comprehensive understanding of pest populations and crop conditions (Zhang *et al.*, 2019). Merging inputs from multiple sensors helps maximize the advantages of each technology while compensating for their individual shortcomings (Yao *et al.*, 2022). This data fusion process combines information from diverse sources to produce more accurate assessments of pest infestations and crop damage. For instance, pairing satellite observations with UAV-collected imagery delivers both broad coverage and fine-scale detail, supporting targeted pest interventions (Yao *et al.*, 2022). Likewise, linking wireless sensor networks with visual recognition systems can yield real-time insights into pest behavior, improving early detection and response to outbreaks (Jiang *et al.*, 2018). Decision support systems (DSS) are essential for converting this wealth of data into practical guidance for pest control. These digital tools bring together information from weather stations, crop growth models, and monitoring networks to generate risk forecasts, economic

thresholds, and management advice (Magarey *et al.*, 2018). When remote sensing data is combined with weather-driven pest models, for example, it can provide timely alerts about potential outbreaks, helping determine when and where to apply control actions (Fleisher *et al.*, 2020). Precision-based pest management methods such as location-specific pesticide use or biological control can be significantly improved through these integrated technologies. By mapping the timing and spread of infestations, these approaches allow treatments to be focused only on affected areas, lowering overall pesticide use and reducing harm to non-target species (Yao *et al.*, 2022). One example is using UAV-derived data to guide the release of beneficial organisms like parasitoids or predators, increasing the precision and success of biological control efforts (Giles *et al.*, 2021). The integration of remote sensing and automated monitoring brings considerable economic and environmental advantages in pest management. Through earlier detection, more precise targeting, and better-informed control strategies, these tools help reduce crop losses, boost yields and quality, and lessen the ecological footprint of pesticides (Zhang *et al.*, 2019). Furthermore, adopting such technologies supports more sustainable and resilient farming systems, contributing to long-term food security and environmental protection (Magarey *et al.*, 2018) ^[5, 9, 27, 28, 31].

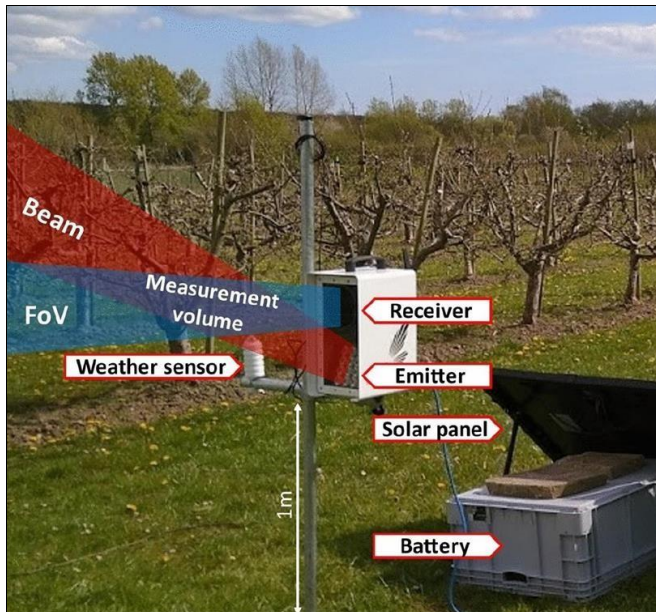


Fig 9: Integration of remote sensing and automated monitoring systems for insect pest detection

5. Challenges and future directions

Although remote sensing and automated monitoring technologies have made notable progress in detecting and tracking insect pests, several challenges and limitations persist. A key technical hurdle lies in creating sensors and platforms that are affordable, dependable, and easy to use, while also being durable enough to operate under the demanding conditions of agricultural environments (Zhang *et al.*, 2019). Widespread implementation further depends on whether these systems can be effectively scaled and adapted across various crops, regions, and pest types (Jiang *et al.*, 2018). Managing and integrating the large volumes of data generated often in different formats remains a major obstacle. Establishing standardized data protocols, consistent metadata practices, and accessible data-sharing platforms is vital for combining and analyzing information from multiple sources (Yao *et al.*, 2022). There is also growing recognition of the need for sophisticated analytical methods, including machine learning and big data approaches, to derive actionable insights from extensive monitoring datasets (Biswas *et al.*, 2022). The extent to which farmers, extension services, and pest management professionals adopt these technologies often hinges on how useful, user-friendly, and cost-efficient they are perceived to be (Zhang *et al.*, 2019). To encourage broader uptake, it is important to design intuitive interfaces, practical decision-support tools, and effective training initiatives (Magarey *et al.*, 2018). Future research should prioritize overcoming these barriers and pushing technological boundaries. Promising developments include low-cost, compact, and energy-efficient devices such as wireless sensor networks and IoT-based systems, which could improve scalability and accessibility (Jiang *et al.*, 2018). Combining remote and automated monitoring with emerging innovations like artificial intelligence, big data analytics, and cloud computing holds strong potential to enhance system performance, flexibility, and decision-making accuracy (Biswas *et al.*, 2022). Another critical area for advancement is the creation of integrated monitoring frameworks that operate across multiple scales, incorporate various sensors, and track multiple pest species simultaneously, enabling a more complete understanding of pest dynamics and crop status (Yao *et al.*, 2022). Embedding ecological knowledge such as interactions between pests and crops, populations of

natural predators, and landscape-level influences can strengthen the predictive ability of these systems and support more sustainable pest control strategies (Fleisher *et al.*, 2020). Additionally, rigorous testing and validation of these technologies across diverse farming systems and environmental conditions are necessary to evaluate their reliability, resilience, and applicability in different contexts (Zhang *et al.*, 2019). Building collaborative research networks, shared data infrastructures, and public-private partnerships will be key to advancing, evaluating, and deploying these tools among varied users and regions (Magarey *et al.*, 2018)^[1, 3, 9, 27, 28, 31].

6. Conclusion: Remote sensing and automated monitoring have become valuable tools for detecting and tracking insect pests in agriculture. Technologies such as satellite imaging, drones, wireless sensor networks, and computer vision enable non-invasive, real-time, and detailed observation of pest activity and crop conditions. When combined with precision farming methods and decision-support systems, these tools can transform pest management by minimizing losses, boosting yields, and supporting sustainable practices. Yet, their broader application faces obstacles, including technical constraints, difficulties in managing and integrating data, limited user adoption, and the need for consistent validation across varied field environments. Ongoing research should aim to overcome these barriers by creating affordable, dependable, and easy-to-use sensors and platforms, incorporating innovations like artificial intelligence and big data analytics, and fostering collaborative research and data-sharing initiatives. Effectively deploying these systems requires interdisciplinary collaboration among entomologists, plant pathologists, agronomists, computer scientists, and engineers. Combining biological and ecological insights with advanced monitoring capabilities is essential for building effective and sustainable pest control strategies. Leveraging these technologies can strengthen agricultural resilience, improve productivity, safeguard food supplies, and contribute to environmental protection for future generations.

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